Inversion of the severity of winter wheat yellow rust using proper hyper spectral index

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Abstract: The objective of this study was to develop the appropriate spectral indices for prediction of yellow rust index that are relatively insensitive to species, canopy structures (such as leaf area index and leaf angle distributions), foliar inner structures, and soil condition variations. When winter wheat was infected with yellow rust, the leaf chlorophyll concentration decreased, the regression equation between SPAD value and measured chlorophyll concentration was established. Canopy reflected spectrum and canopy chlorophyll concentration were measured during growth duration, it indicated that it had the logarithmic relationship between the ratio of Transformed Chlorophyll Absorption in Reflectance Index (TCARI) to Optimized Soil Adjusted Vegetation Index (OSAVI) and Minolta Chlorophyll Meter (SPAD) value, with a coefficient of determination $R^2 = 0.7795$ ($n = 320$), so the combined index TCARI/OSAVI was proved to be sensitive to chlorophyll concentration and very resistant to the other variations such as Leaf Area Index (LAI) and no photosynthetic materials at canopy level. Therefore, the predictive capability of TCARI/OSAVI seems consistent and satisfactory. The proper reflectance index of photochemical reflectance index (PRI) was chosen for disease index inversion by minimizing foliar inner structure effect, it has linear negative relationship between the normalized photochemical reflectance index (NPRI) and disease index (DI), with a coefficient of determination $R^2 = 0.8477$ ($n = 63$), so the normalized photochemical reflectance index (NPRI) can be used to monitor the disease index of yellow rust.

Key words: yellow rust; inversion; disease index; hyperspectral index; winter wheat (*Triticum aestivum* L.)

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0 Introduction

Winter wheat (*Triticum aestivum* L.) is one of the most important crops in China. The yield gradients, however, caused by yellow rust, approximately 73%～85% of the whole yield loss, grain quality indicators (such as protein content) were greatly decreased. It is highly desirable to develop new techniques to overcome the limitations of traditional field survey methods for crop health monitoring, hyperspectral remote sensing can play a vital role in providing time-specific and time-critical information for crop growth monitoring, due to their capabilities in measuring canopy reflected spectrum. Some researchers have studied the relationship between spectral characteristics and biochemical and biophysical indices. Wang (2002) assessed the quality indicators by foliar nitrogen content at anthesis stage. Carter (1994) studied the ratios of leaf reflectance in narrow wavebands as indicators of plant stress. Rinehart (2002) studied the relationship between canopy spectral reflectance of stripe patch and dollar spot severity on creeping bentgrass. Shibayama (1990) estimated rice grain yield using hyperspectral data. But, study on inversion of disease index (DI) from canopy reflected spectrum up to now is slim.

Plant disease detection based on canopy reflected spectrum relies on the properties of light emerging from the canopy after multiple interactions, i. e., reflectance, transmissions, and absorptions, with the tissues of plant and the characteristics of soil and environments. The winter wheat canopy reflected spectra are the mixed spectra in view of the sensor, which are affected by wheat canopy (leaf area index and leaf angle distribution, leaf water content,

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mineral deficiencies, parasitic attacks, and so on), soil (soil properties, soil illumination), weeds (weed species, amounts), environment and their interactions. Healthy leaves typically exhibit low reflectance at visible wavelengths (400～700 nm) owing to strong absorption by photoactive pigments (chlorophylls, anthocyanins, carotenoids); high reflectance in the near infrared (700～1200 nm) due to multiple scattering at the air-cell interfaces in the leaf internal tissue; low reflectance in wide wavebands in the short-wave infrared (1200～2400 nm) due to absorption by water, proteins, and other carbon constituents (Jacquemoud S, and Ustin S. L., 2001; Wooley J. T., 1971). Disease can cause changes in leaf transpiration rate, leaf color, morphology, and crop density, which in turn affect the optical properties of the canopy. For example, reflectance changes in violet-blue and near infrared wavebands (380～450 nm and 750～1200 nm) were used to detect early infections of cucumber leaves by the fungus Colletotrichum orbiculare (Sasaki, 1998). Indeed, optical changes have been used for many years to visually assess disease disk, but such assessments by the farmer/extension worker are time-consuming and can be inaccurate (Paker 1995). Hyperspectral imaging systems scan a large number of wavebands, thus providing a greater spectral resolution in a cost-effective manner (Lamb and Brown, 2001). Studies using hand-held spectroradiometers have demonstrated the potential of hyperspectral measurements in detection of weeds (Brown et al, 1994). Disease control could be more efficient if disease patches within fields could be identified, spray applied only to the infected areas and for yield loss forecasting. It is the multifactor interaction complexity, responsible for canopy reflected spectrum variability under different stress conditions, which inspired this work on developing a methodology for an accurate estimation of disease index by canopy reflected spectrum.

1 Methodology

1.1 Experimental site

The experiment was conducted at remote sensing base of Beijing suburb, which is located in Changping district (40°10.6′N, 116°26.3′E), from the year of 2001～2002 and 2002～2003. The site is at the warm temperate zone with a mean annual rainfall of 507.7 mm and a mean annual temperate of 13℃.

1.1.1 Soils

Wheat was planted in a silt clay loam soil, the nutrients of surface soil (0～30 cm) were as follows: the organic matter, 1.42%～1.48%; total nitrogen, 0.081%～0.100%; alkali-hydrolysis nitrogen, 58.6～68.0 mg/kg; available phosphorus, 20.1～55.4 mg/kg and available potassium, 117.6～129.1 mg/kg.

1.1.2 Cultivars

Three winter wheat (*Triticum aestivum* L.) cultivars ('Jing 411', '98-100', and 'Xuezao') were selected. Jing411 has stiff straw with a high tolerance to yellow rust, 98-100 has moderate tolerance to yellow rust, Xuezao was susceptible to yellow rust.

1.2 Treatments

In order to distinguish spectral differentiation of yellow rust from other environmental factors stress, the different stress treatments were chosen as follows:

Normal treatment (CK) was treated with the normal winter wheat production management in North China.

Nitrogen deficiency was no nitrogen fertilization during the crop growing season (from seeding to harvesting), the soil conditions, irrigation and other managements are the same as the normal treatment.

Drought was under no irrigation from heading to harvesting stage; the soil conditions and other managements are the same as normal treatment.

Yellow rust was inoculated by the yellow rust epiphyte according to plant protection standard, and disease index data were gained in field at an interval of 5 days after inoculation.

Fungicide, spraying normal heathy growth winter wheat with maximum permissible concentration fungicides.

Aphides, aphides were one of major insect pests of winter wheat in China, it burst out naturally.

1.3 Measured item and methods

Disease indexes were gained by the field survey, reflected spectrum were acquired by ASD FieldSpec Pro spectrometer, at the same time, various field and laboratory data were collected for biochemical and biophysical parameters analysis by the standard measuring methods (Zhang, 1994), which including chlorophyll concentration, total nitrogen, relative water content and leaf area index (LAI) etc.

Spectral index: Driss (2002) presented a combined modeling and index for predicting chlorophyll concentration from canopy reflected spectrum while minimizing LAI influence and underlying soil background effects. The index was defined as transformed chlorophyll absorption reflectance index/optimized soil-adjusted vegetation index (TCARI/OSAVI). It was defined as follows:

$$TCARI = 3[(R_{700} - R_{670}) - 0.2(R_{700} - R_{550})(R_{700}/R_{670})]$$

$$OSAVI = (1 + 0.16)(R800 - R670)/(R800 - R670 + 0.16)$$

Where TCARI is ameliorated from Modified Chlorophyll Absorption in Reflectance Index (MCARI), which was proposed by Daughtry (2000) as a variant of the Chlorophyll Absorption in Reflectance Index (CARI) developed by Kim (1994). TCARI is resistant to non-green biomass effects, but it is still sensitive to the underlying soil reflectance properties, particularly for low LAI (Rondeaux, 1996). In order to overcome this problem, Daughtry (2000) proposed the MCARI be combined with a soil line vegetation index like Optimized Soil-Adjusted Vegetation Index (OSAVI, Rondeaux, 1996). OSAVI belongs to the Soil-Adjusted Vegetation Index (SAVI; Huete, 1988).

Photochemical reflectance index (PRI) was defined by Peñuelas (1995) as follows:

$$PRI = (R_{531} - R_{570})/(R_{531} + R_{570})$$

Where Rx corresponds to the reflectance at the wavelength considered. Leaf pigments of the xanthophylls cycle play a major role in light absorption at 531 nm; the 570 nm was used to reduce the chloroplast movements.

2 Data

2.1 Disease index and disease leaf rate (DLR)

Disease index (DI) was gained at an interval of 5 days after inoculation. And the disease severity degree was classified into nine different levels, 0, 1 percent, 10 percent, 20 percent, 30 percent, 45 percent, 60 percent, 80 percent, and 100 percent, it was the ratio of the yellow rust patch areas to the whole leaf areas, the DI can be calculated as the following formula:

$$DI = \frac{\sum (x \times f)}{n \times \sum f} \times 100$$

Where x is the disease severity degree; n is the highest-level magnitude, which is 8; it was referred to Li's research (Li, 1989).

Disease leaf rate (DLR) data were defined as the ratio of disease leaf numbers to the total leaf numbers in a unit field area.

2.2 Foliar spectral data

Foliar spectral data were measured by LI-Cor1800-12S External Integrating Sphere, which was coupled with ASD Field Spec Pro FR 2500 (350～2500 nm).

2.3 Field canopy spectral data

All canopy spectral measurements were taken from a height of 50 cm above canopy under clear blue sky conditions between 10：00 and 14：00 at local time, using an ASD FieldSpec Pro spectrometer (Analytical Spectral Devices, Boulder, CO, USA) fitted with 25° field of view fiber optics, which functions in the 350～2500 nm spectral region with spectral resolution of 3 nm at 700 nm, 10 nm, 1400 nm and 2100 nm, and with a sampling interval of 1.4 nm between 350 and 1050 nm, and 2 nm between 1050 and 2500 nm. Reflected spectrum was used for calculation by a 0.40 m × 0.40 m $BaSO_4$ calibration panel. Vegetation and panel radiance measurements were taken by averaging 20 scans at optimized integration time with due care for dark current correction at every spectral measurement. It was measured at an interval of 7 days.

2.4 Biophysical and biochemical parameters

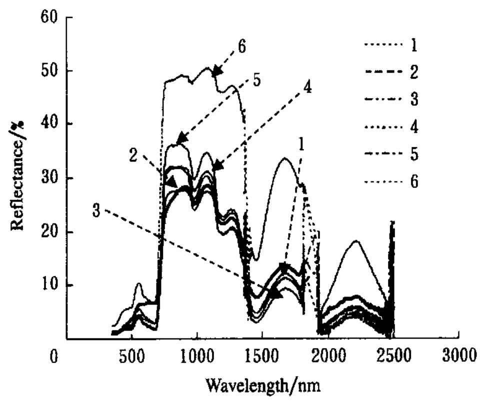
Immediately following each canopy reflectance measurement, the precise area are corresponding to the footprint of the field spectrometer was harvested to soil level, packed in cooled black plastic bags and transported to the laboratory for subsequent analysis. Various field and laboratory data were collected for biochemical and biophysical analysis, such as foliar chlorophyll, foliar nitrogen and leaf area index (LAI) etc. Leaf samples and stem samples were immediately weighed to determine fresh biomass, dried separately in a forced drought oven for 48 h at 70℃ and weighed again to determine dry biomass. Leaf water content per unit leaf area was calculated as the difference between leaf fresh and dry mass. Foliar nitrogen concentration expressed as a percentage of leaf dry weight, was determined by Kjeldahl digestion and subsequent determination of ammonia by distillation method. Foliar chlorophyll concentration was measured by two kinds of methods (chlorophyll meter and traditional methods of pigment analysis), the chlorophyll concentration was first measured by a hand-held chlorophyll meter which is called SPAD-502 (Specialty Products Agriculture Division, Minolta Corporation), it works at 650 nm and 940 nm with two light emitting diodes. To record reading displayed in SPAD units, leaf was inserted at about half way from the leaf tip and collar, and about middle point between leaf midrib and leaf margin. After measuring by SPAD-502, it was measured spectrophotometrically after extraction with 80% acetone, according to Arnon method. Before tasseling stage the newest fully expanded leaf, which had an exposed collar was chosen for measurement. After tasseling stage the flag leaf was chosen for biochemical variables (foliar nitrogen, foliar chlorophyll etc.) measurement. Leaf area index was measured by passing all leaves through an area meter (LI-3100, LI-COR, Lincoln, NE).

3 Results

3.1 Hyperspectral differentiation of nitrogen deficiency, yellow rust, aphides, drought and fungicide

In order to study the yellow rust from canopy reflected spectrum, the canopy spectrum of yellow rust from environmental stress factors should first be distinguished. Environmental stress factors were classified into nitrogen deficiency, drought, yellow rust, pesticide and aphides.

As shown in Fig. 1, the canopy reflectance of aphides increased in near infrared bands because the foliar surface was covered by aphides. The canopy reflected spectrum of fungicide, drought and nitrogen deficiency are all increased in visible bands and decreased in near infrared bands compared to normal (CK). The reflectance of yellow rust increased slightly in visible bands and decreased in near infrared. Though the spectrum has differentiation between different stress factors, but it is hard to distinguish by original canopy reflected spectrum, some further work for the extraction of yellow rust information from canopy spectrum should be carried out.



1. Nitrogen deficiency 2. Drought 3. Yellow rust 4. Fungicide 5. Normal 6. Aphides

Fig. 1 Canopy reflectance of normal, yellow rust, aphides, drought, nitrogen deficiency and fungicide poison

3.2 Relationship between SPAD value and measured chlorophyll concentration

The amount of chlorophyll per unit leaf area of winter wheat is a good indicator of crop healthy conditions. Therefore, determination of leaf chlorophyll concentration can be used to detect plant mutations, stress, and nutritional state. The standard method for determining leaf chlorophyll concentration is to homogenize the leaf tissue in 80% acetone, measure the absorbance at 663 and 645 nm, and then calculate the chlorophyll concentration using the specific absorption coefficients for chlorophyll a and b (Arnon, 1949). Although this method works well, it has two drawbacks. First, this method is time consuming, especially when there are numerous specimens to analyze. Secondly, the leaf specimen was destroyed, thus making further study of that specimen impossible. The Minolta Chlorophyll Meter SPAD-502 can be used to rapidly determine chlorophyll concentrations in plant leaves without damage to the leaf. Initially, one was limited to the arbitrary units, which the instrument displays. However, the data and graphs presented in this paper show that there is a linear relationship between the SPAD values and the total chlorophyll (calculated by conventional methods) in winter wheat leaves. The measured leaves ranged from erecting to maturity growth stages, and the measured leaf included different growth stages, different leaf color (green, yellow-green, yellow etc.).

This relationship makes it possible to use the graph as a standard curve and determine actual amounts of chlorophyll per unit area from SPAD values. The method presented in this paper can be used to construct standard curves for other species of plants, which may not correlate directly to the measured data due to differences in leaf thickness and morphology.

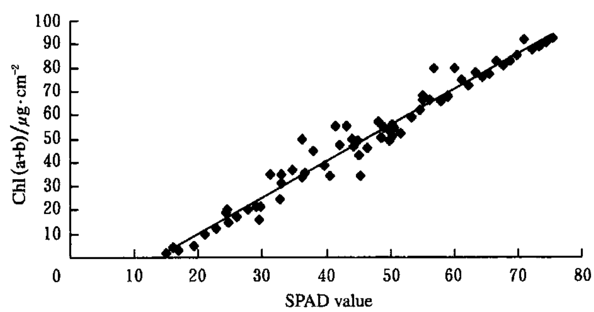


Fig. 2 Relationship between SPAD value and total chlorophyll concentration

3.3 Application of TCARI/OSAVI to chlorophyll concentration estimation to minimize leaf area index and soil background effect

Some researchers indicated that LAI plays an important role in canopy reflected spectrum; the LAI dominated the near infrared spectral characteristics of canopy reflected spectrum. In order to inverse canopy chlorophyll concentration, the effect of LAI on canopy reflected spectrum should be eliminated. Chlorophyll concentration is an indicator of photosynthesis activity, which is related to the nitrogen concentration in green vegetation and serves as a measure of crop response to nitrogen application.

This paper introduced the use of the ratio TCARI/OSAVI to make accurate predictions of winter wheat chlorophyll concentration, canopy reflected spectrum and chlorophyll concentration were acquired for about 80 days intervals, which covered the five different growth stages. The SPAD value ranges from 18 to 108. As shown in Fig. 3, relationship was established between measured chlorophyll concentration (in laboratory) and the ratio of TCARI/OSAVI derived from canopy reflectance data. The canopy spectrum and the canopy chlorophyll concentration were acquired for almost all the growth duration, it lasted about 70 days covered the winter wheat major yield and grain quality contribution growth stages (such as erecting stage, elongation stage, heading stage, anthesis stage, early grain filling stage, middle grain filling stage, late grain filling stage, wax ripeness stage). It indicated that it has the logarithmic relationship between the TCARI/OSAVI and the SPAD value, with a coefficient of determination $R^2 = 0.7795$ ($n = 320$), so the combined index (CCII) can be used to minimize the effects of LAI and no photosynthetic materials on the retrieval of chlorophyll concentration at canopy level. Therefore, the predictive capability of TCARI/OSAVI seems consistent and satisfactory.

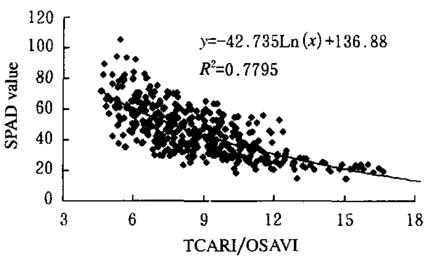


Fig. 3 Relationship between measured chlorophyll concentration and the ratio of TCARI/OSAVI

3.4 Relationship between disease index and disease leaf rate

The stripe rust disease index can be used to denote the disease serious degree, it was the ratio of yellow rust patch areas to the whole leaf areas, and it was classified into 9 different levels, which was defined by crop protection experts. DI should be gained by field survey, it is time consuming and it is difficult for some farmers to do this in the field. So some simple disease index field survey method should be found for the inversion of yellow rust in the filed. As shown in Fig. 4, the disease leaf rate was saturated when the disease index was more than 20%, it has linear correlation between DI and DLR at early stage of yellow rust, it is still in the prevention and cure stage.

3.5 Application of photochemical reflectance index (PRI) for disease index inversion by minimizing foliar inner structure effect

Some physiological reflectance indices such as photochemical reflectance index (PRI) were proposed to predict the biochemical concentration. Because when the winter wheat was inoculated by yellow rust epiphyte, as time went on the foliar pigments were destroyed and foliar physiological properties decreased, so the PRI was chosen to monitor disease index. Since the PRI value in this research is too small, it was necessary to scale PRI; in this paper the normalized photochemical reflectance index (NPRI) was defined as the value of PRI times 100. As shown in Fig. 5, It has the linear negative relationship between the NPRI and DI, with a coefficient of determination $R^2 = 0.8477$ ($n = 63$), so the normalized photochemical reflectance index (NPRI) can be used to forecast the disease index of yellow rust.

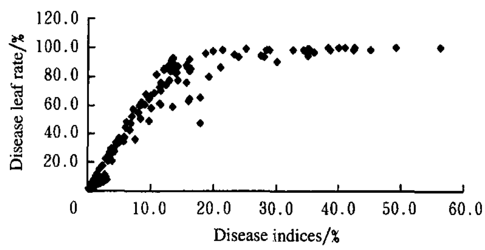


Fig. 4 Relationship between disease index (DI) and disease leaf rate (DLR)

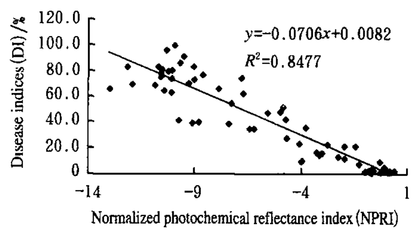


Fig. 5 Relationship between normalized photochemical reflectance index and disease index

4 Discussion and conclusion

The objective in this study was to develop the appropriate spectral index for prediction of yellow rust index that is relatively insensitive to wheat canopy (leaf area index and leaf angle distribution, leaf water content, mineral deficiencies, parasitic attacks, and so on), soil (soil properties, soil illumination), weeds (weed species, amounts), environment and their interactions. The different canopy structures (Jing 411, the erective cultivar; Xuezao, the middle cultivar; 98- 100, the loose cultivar) were classified by leaf obliquity distribution characteristics. Young, mature and senescent leaves were collected from the 3 varieties that varied greatly in structural variations on the relationship between canopy biochemical variables and spectral indices.

When winter wheat was infected with yellow rust, the leaf chlorophyll concentration decreased, it has good relationship between SPAD value and measured chlorophyll concentration. The method presented in this paper can be used to construct standard curves for other species of plants, which may not correlate directly to the measured data due to differences in leaf thickness and morphology. Furthermore, it may be possible to assign real parameters to the color classifications that are now typically determined visually. On the other hand the regression equation between measured chlorophyll concentration (in laboratory) and the ratio of TCARI/OSAVI derived from canopy reflectance data was established, with a coefficient of determination $R^2 = 0.7795$ ($n = 320$), so the ratio of TCARI/OSAVI can be used to minimize the effects of LAI and no photosynthetic materials on the retrieval of chlorophyll concentration at canopy level.

The proper reflectance index of photochemical reflectance index (PRI) was chosen for disease index inversion by minimizing foliar inner structure effect, it has linear negative relationship between the normalized PRI and DI, with a coefficient of determination $R^2 = 0.8477$ ($n = 63$), so the normalized photochemical reflectance index (NPRI) can be used to forecast the disease index of yellow rust.

As suggested above this can be done within a geographic information system (GIS) environment that makes all observations spatially explicit, the first is through the use of a convergence of indicators: combining remote sensing data with other independent observations (e.g., growing season outlook from satellite data combined with field survey on the ground). The second, and more expensive, alternative is an orchestrated campaign of ground sampling in support of remote sensing data acquisition. The third is to incorporate remote sensing data and disease index as in input into predictive models of behavior. With supporting of GIS, the winter wheat growth variables, soil variables, weather conditions, field disease index survey data, canopy reflected spectrum data can be managed by GIS, and disease infection degrees and broadcasting areas can be promulgated by the website. Based on this technology, it is possible for the dynamic, expeditious and nondestructive way to gather winter wheat disease information in a relatively wide area in a short-term duration.

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利用高光谱指数进行冬小麦条锈病严重度的反演研究

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摘　要: 通过选取不同条锈病抗性品种(高抗、高感、中间)进行田间不同梯度(对照、轻度、中度、重度)的接种试验, 在接种后每隔 7 d 左右, 同步测定了不同品种、不同处理的冠层光谱、单叶光谱和对应目标的病情指数以及叶面积指数、叶倾角等生物物理参数和叶绿素、SPAD 数值等生物化学参数。通过对获取的光谱数据和生物物理参数和生物化学参数进行统计分析。研究结果表明, 小麦被条锈病感染以后, 叶片叶绿素含量急剧下降, 通过研究叶片绿度值(SPAFD)值与叶绿素含量之间的关系, 建立了叶片叶绿素含量和叶片 SPAD 数值之间的线性关系方程。通过在借鉴前人研究结果的基础上, 通过筛选光谱指数, 在冠层水平上构建作物冠层结构不敏感色素反演指数(CCII= TCARI/OSAVI)来反演全生育期不同处理的 SPAD 数值, 此反演结果受品种类型、冠层结构和土壤背景的影响较小, 线性方程的决定系数达到极显著的水平。在单叶水平选取归一化的光化学指数(NPRI)来反演单叶的病情指数(DI), 线性方程的决定系数达到极显著的水平。所以该文通过选取适当的高光谱指数进行冬小麦条锈病严重度的反演的理论和方法是可行的。且反演结果受不同品种、不同叶面积指数和土壤背景等的影响均较小。

关键词: 条锈病; 反演; 病情指数; 高光谱指数; 冬小麦